Do Neighborhood Dynamics Influence Heat Vulnerability in Chicago? Lessons from the 1995 Chicago Heat Wave

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Introduction

The 1995 Chicago Heat Wave was an extraordinarily deadly summer event that claimed the lives of more than 700 Chicagoans over a one-week period in July. Although unprecedented weather conditions, including persistent high temperatures and humidity, combined to produce the Chicago Heat Wave, examination of mortalities demonstrates the event was a socially organized disaster. Victims were often found to be poor, elderly, and living alone. Neighborhoods with the highest mortality rates tended to have a high proportion of elderly residents and high levels of poverty and violent crime. The geography of heat wave mortality largely mirrored the geography of concentrated poverty and disinvestment in Chicago. Clearly, individual and place-based factors were acting to increase the risk of heat-related death. Mortality data from the Chicago Heat Wave provides an opportunity to examine the degree to which DNT Neighborhood Typology, a composite measure of neighborhood-level factors, serves as an appropriate indicator of heat vulnerability.

The relationship between neighborhood type and heat vulnerability in the context of the 1995 Chicago Heat Wave was prominently asserted by sociologist Eric Klinenberg in his 2002 book, "Heat Wave: A Social Autopsy of Disaster in Chicago." In addition to presenting evidence supporting the causality of individual risk factors, Klinenberg identified additional place-based factors that appeared to increase the risk of mortality during the heat wave event. These include high rates of violent crime, limited access to everyday resources, and a dearth of social and commercial attractions. Klinenberg posited that these neighborhood-level characteristics converged to produce isolation and reclusiveness, and that this neighborhood dynamic could ultimately explain the differences in mortality observed between neighborhoods with similar proportions of vulnerable residents (Klinenberg 2002). In examining the suitability of neighborhood typology as a predictor of heat vulnerability, this paper aims to use this measure to capture the neighborhood dynamics described by Klinenberg, and ultimately produce findings that affirm or negate his hypothesis.

Establishing a link between neighborhood typology and heat vulnerability will have several implications for emergency management and hazard mitigation planning within the City of Chicago. DNT Neighborhood Typology can provide an "actionable" data-based reference for policymakers during multi-phase emergency planning for heat wave events. This would be an improvement over existing heat vulnerability indices, whose interpretations are limited primarily to comparative purposes (Reid 2009). By intuitively communicating neighborhood dynamics to policymakers, neighborhood typologies can facilitate the preparation of neighborhood-specific response plans and inform real time decision-making when facing unexpected circumstances. Furthermore, the unique properties of DNT typology that allow it to function as tool for designing economic development interventions can translate into similarly useful applications for the purposes of heat-related emergency management and land use planning in Chicago.

This paper first summarizes literature regarding heat vulnerability, including demonstrated and theorized individual and place-based factors. A description of the methodology used to conduct an analysis of mortality attributed to the 1995 Chicago Heat Wave is given. The analysis itself follows and is comprised of spatial, graphical, and statistical components. A discussion regarding the relationship between neighborhood type and heat wave vulnerability summarizes and interprets outcomes from the mortality analysis. Findings from the analysis are then used to inform policy recommendations to improve the performance of emergency management and hazard mitigation strategies for future heat events within the City of Chicago.

Review of Heat Vulnerability Literature

Heat-Related Health Risks

Prolonged exposure to extreme heat results in heat stress, which may lead to death if the exposure is severe enough (Luber 2006). Accordingly, days with higher-than-average temperatures and periods of extended high temperatures have been demonstrated to increase heat-related mortality (Chestnut 1998). However, not all populations face the same health risks during heat events. A range of individual and place-based factors have been shown to affect the likelihood of heat-related illness and/or death.

Individual Factors

Several socioeconomic characteristics are likely to increase an individual's risk of heat-related health consequences. These include a person's age, income, education, and race. To begin with, the elderly have demonstrated higher mortality and hospital admission rates during heat waves (Stafoggia 2006; Knowlton 2009). Poverty has been shown to modify the effects of heat. During a 1999 heat wave in Chicago, a modest increase in the risk of heat-related death was observed for those making less than $10,000 (Naughton 2002). A study conducted in Seoul, Korea also found low-income people had higher mortality rates during hot weather (Kim and Joh 2006). Low educational attainment has also been shown to affect risks of heat-related deaths. Studies of U.S. cities found individuals with at most a high school education experienced heat-related deaths at a rate higher than those with more years of education (Medina-Ramon 2006). Lastly, non-white populations were found to be at greater risk of heat-related death. A 2001 study from the Center for Disease Control (CDC) found that blacks had a higher age-adjusted heat-related death rate than whites throughout the U.S. from 1979 to 1998 (CDC 2001).

Individual risk factors unique to heat events have also been identified. These concern a person's health, use of air conditioning, and living arrangements. Several preexisting health conditions, including cardiovascular disease and diabetes, may lead to susceptibility to heat-related illness and death (Naughton 2002; Schwartz 2005). Meanwhile, air conditioning can serve as strong protection against heat-related deaths. Both room and central air conditioning are negatively correlated with heat-related mortality (Chestnut 1998). Lastly, living alone was found modify the risks of heat-related death. A study of the 1999 Chicago heat wave found that people who lived alone had a higher risk of death compared with people with more social contacts (Naughton 2002).

The contributions of the aforementioned individual factors to heat vulnerability in the U.S. are well recognized, given that comparable variables were all included in the Heat Vulnerability Index, which was composed in 2009 for the purposes of mapping national heat vulnerability at the census tract-level. Index values were calculated using ten variables shown to increase vulnerability to heat-related health affects in urban areas and for which national data sets were available.

(See Appendix 1 for a description of the methodology underlying the Heat Vulnerability Index). These included the proportion of the population (1) aged 65 or older, (2) living in poverty, (3) with less than a high school diploma, (4) self-identified as non-white, (5) diagnosed with diabetes, (6) without central air conditioning, (7) without any kind of air conditioning, (8) living alone, and (9) aged 65 or older and living alone. Of the ten variables considered for the Heat Vulnerability Index, only one, the proportion of land area without vegetation, was not an individual risk factor, but rather a place-based factor (Reid 2009).

Previous analyses of mortality data from the 1995 Chicago Heat Wave confirmed several of the individual factors generally identified in heat vulnerability literature served as appropriate indicators of heat-related mortality for this specific heat wave event. This includes the proportion of the population: (1) aged 65 or older, (2) living in poverty, (3) self-identifying as African-American, (4) without air conditioning, (5) living alone, and (6) aged 65 or older and living alone. Mortality demographics demonstrated that the elderly and African-Americans faced a significantly higher likelihood of death during the 1995 Chicago Heat Wave. Seventy-three percent of heat-related casualties were found to be people 65 years or older. African-Americans had the highest proportional death rates of any ethnic and/or racial group, and in fact the mortality rate for African-Americans was 50% higher than whites (Klinenberg 2002). An association between high poverty rates and high mortality rates was also observed. Seven of the 15 neighborhoods with the greatest number of heat-related deaths had poverty rates that placed them in the top quintile of Chicago's poorest communities (Klinenberg 2002). Furthermore, an epidemiological investigation of the 1995 Chicago Heat Wave conducted by the U.S. CDC found a lack of air conditioning and living alone to be two of several individual factors that increased the likelihood of death during the heat wave crisis (Klinenberg 2002). Lastly, an additional association between a high proportion of elderly persons living alone and high mortality rates was observed. Four of the 15 community areas with the greatest number of heat-related deaths were in top 20% of communities with regards to percentage of persons aged 65 or older and living alone (Klinenberg 2002).

Place-Based Factors

Much fewer factors related to the built environment have been found to influence the rate of heat-related health consequences. These include community-level characteristics related to land cover and housing markets. Because areas with a high degree of impervious land cover contribute to the heat island effect, they tend to experience exaggerated health effects during a heat wave event (Clarke 1972). Accordingly, the availability of green space is associated with a decreased risk of heat-related illness and death. A study of the 1980 heat wave in St. Louis found incremental increases in greenery surrounding residences were associated with a significant decrease in the risk of heat stroke (Kilbourne 1982). A high number of vacant housing units can also pose increased heat risks. Neighborhoods with a high proportion of vacant housing in Philadelphia and Phoenix were associated with higher rates of heat distress calls and mortality (Uejio 2011). Poor housing conditions have also been shown to amplify the risk of heat-related health impacts. A study of heat-related mortality in New York City found that areas with higher rates of poor quality housing, as indicated by code violations and property tax delinquencies, were associated with higher mortality rates (Rosenthal 2014).

The influence of place-based factors on heat vulnerability in the U.S. appears to be less recognized than that of individual factors. As noted before, only one of the ten variables considered for the Heat Vulnerability Index was a place-based factor. This variable, the proportion of land area without vegetation, was chosen to represent the demonstrated effects of land cover composition on heat-related health consequences (Reid 2009). However, the significance of two place-based factors on heat-related mortality has been confirmed for the 1995 Chicago Heat Wave event. A study of mortality data from the event affirmed two variables related to land cover served as appropriate indicators of heat-related mortality. The normalized difference vegetation index (NDVI), a measure of vegetation abundance, and normalized difference built-up index (NDBI), a measure of the abundance of components indicative of the built environment, accounted for about 12% of the variance in vulnerability throughout the city (Johnson 2012).

In “Heat Wave: A Social Autopsy of Disaster in Chicago”, Klinenberg contends that additional place-based factors may have increased the risk of mortality during the 1995 heat event in Chicago. These include rates of violent crime at the neighborhood-level and a “lack of access to everyday resources.” He described the latter as the dearth of “social and commercial attractions that draw people outdoors”, such as animated public spaces, and providers of food and medicine. As Klinenberg explains, violent neighborhood crime “pushes” older residents to remain at home, while lack of access to everyday resources fails to provide a great enough “pull” for them to venture outside of their residences. These two forces work in tandem to produce isolation (limited social ties) and reclusiveness (confinement to the household), which make older residents less likely to receive or be able to reach aid during a heat wave event (Klinenberg 2002). Klinenberg provides some evidence that neighborhood crime may have increased the risk of mortality during the 1995 Chicago Heat Wave. Seven of the 15 community areas with the highest mortality rates had violent crime rates that placed them in the top 20% of community areas in Chicago ranked according to their violent crimes rates (Klinenberg 2002). However, evidence that links “access to everyday resources” and heat wave mortality is harder to find, mostly due to the fact that there is no clear definition for lack of access to everyday resources. Simple indicators of access to everyday resources could include the number of neighborhood commercial business within a given radius or a Walk Score, which measures the walkability of addresses by considering walking distances to a range of amenities (Walk Score 2016). Although the neighborhood dynamics described by Klinenberg as fostering isolation and reclusiveness cannot be easily measured, this paper will use a comprehensive variable—DNT neighborhood typology—as an indicator for community-specific conditions to assess Klinenberg’s explanation of intra-city variability in heat-related mortality.

Methodology

Data Sources

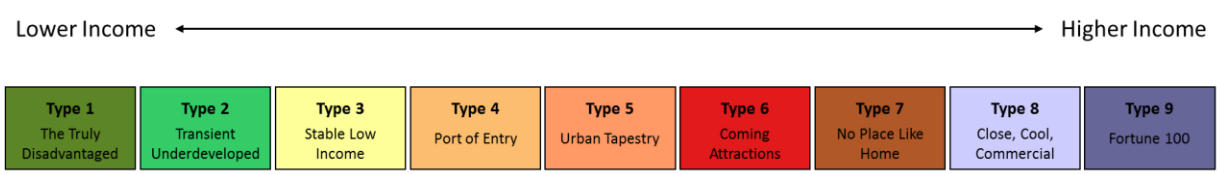
Analysis of the relationship between neighborhood type and heat wave mortality used spatial and qualitative data from three sources:

- US Census TIGER/Line Shapefile (2000)

Geographic boundary files for census tracts in Cook County, IL were downloaded from the U.S. Census web interface for TIGER/Line Shapefiles.

- DNT Neighborhood Typology (2000)

Neighborhood typology data for Chicago census tracts was sourced from the Dynamic Neighborhood Taxonomy (DNT) project, which was completed in 2009 under the leadership of Living Cities and RW Ventures. DNT Neighborhood Typology uses hybrid hierarchical clustering to group neighborhoods from four major cities—Chicago, Cleveland, Dallas, and Seattle—into nine broad types and 33 detailed sub-types (Weissbourd, Bodini, and He 2009). Figure 1 provides a synopsis of the primary layer of the DNT typology, which consists of nine broad neighborhood types ordered according to their median income. Profiles of the nine broad neighborhood types, which include high-level descriptions and details on factors that characterize each neighborhood type, are available in Appendix 2.



Source: *Dynamic Neighborhoods: New Tools for Community and Economic Development* (page 117)

Figure 1: Overview of DNT Neighborhood Typology

The DNT Neighborhood Typology was constructed following a detailed analysis of patterns and drivers of neighborhood change during a 15-year period from 1990 to 2005. The project considered over 2,500 variables for more than 2,000 census tracts, and eventually identified 23 different variables as key determinants of neighborhood type (Weissbourd, Bodini, and He 2009). See Appendix 3 for a heat map illustrating DNT neighborhood types according to the 23 selected indicators.

The DNT Neighborhood Typology was designed to inform economic development interventions by allowing policymakers to tailor interventions to the needs and opportunities of specific neighborhood types, anticipate and manage neighborhood change, and facilitating impact analysis through the identification of comparable neighborhoods (Weissbourd, Bodini, and He 2009). These applications suggest the DNT typology may provide a similarly useful "actionable" data set for emergency managers and land use planners who seek to prepare for and mitigate against the effects of heat events.

- Mortality Data from the 1995 Chicago Heat Wave

Data on deaths attributed to the 1995 Chicago Heat Wave was sourced from the "Heat Wave: An Oral History" webpage. A text file was extracted from the source code for a series of maps illustrating the distribution of victims through the City of Chicago. The text file compiled information provided by the Cook County Medical Examiner's Office on more than 600 people identified as victims of the 1995 Heat Wave. This included characteristics on individuals such as their name, gender, race, age, date of death, street address, and the latitude and longitude coordinates of their street address (Thomas 2015). The validity of this data was confirmed by cross-referencing summed counts of individual heat wave victims with neighborhood-level mortality data presented in *Heat Wave* (Klinenberg 200).

Data Transformation

Geocoding Addresses from Mortality Data

The original text file of mortality data associated with the 1995 Heat Wave provided the street addresses, and corresponding geographic coordinates, of 624 deceased individuals. These residential locations were assumed to be their places of death. In order to spatially locate address data for use in ArcGIS, the text file was converted into an Excel file and geocoded using ArcGIS Online services. Geocoding transformed the given location descriptions, in this case street addresses, into a point shapefile compatible with ArcGIS. The addresses of all 624 individuals were successfully geocoded.

Joining Geographic Boundaries Shapefile and Typology Data

DNT Neighborhood Typology data for the City of Chicago was made available in an Excel file, which assigned one of nine broad neighborhood typologies to 850 census tracts located within the city. The polygon TIGER/Line shapefile for Cook County, IL provided the geographic boundaries of 1,344 census tracts in accordance with the 2000 U.S. Census. ArcMap was used to join the TIGER/Line shapefile and DNT typology data file according to a common attribute field—geographic identifiers for census tracts. Census tracts that did not have an assigned neighborhood typology were eliminated. Thus, this analysis only considered the 850 census tracts in Chicago that had an assigned DNT typology.

Counting Number of Deaths Per Census Tract

ArcMap was used to create a "Count" field in the attribute table of the shapefile of geocoded addresses. A join was performed between the polygon TIGER/LINE shapefile (with associated DNT typologies) and the point shapefile of addresses. The resulting polygon shapefile contained a "Sum_Count" field that indicated the number of point features (heat wave victims) located within each polygon feature (census tract). Point data that located heat wave victims outside of the 850 census tracts with assigned typology were eliminated. Thus, this analysis only considered the 538 victims who were found within the 850 census tracts in Chicago with assigned DNT typologies. The resulting output file, which included the DNT typology and number of victims assigned to each census tract, was exported as CSV file.

Performing Regression Analyses

The exported master file was opened in Excel, which was used to create a series of dummy variables for an array of regression analysis scenarios that were performed using STATA. The regression analyses performed are described in detail in the analysis section of this paper. Complete STATA outputs for those regressions can be found in Appendices 4-7.

Analysis of Mortality Risk with DNT Neighborhood Typology

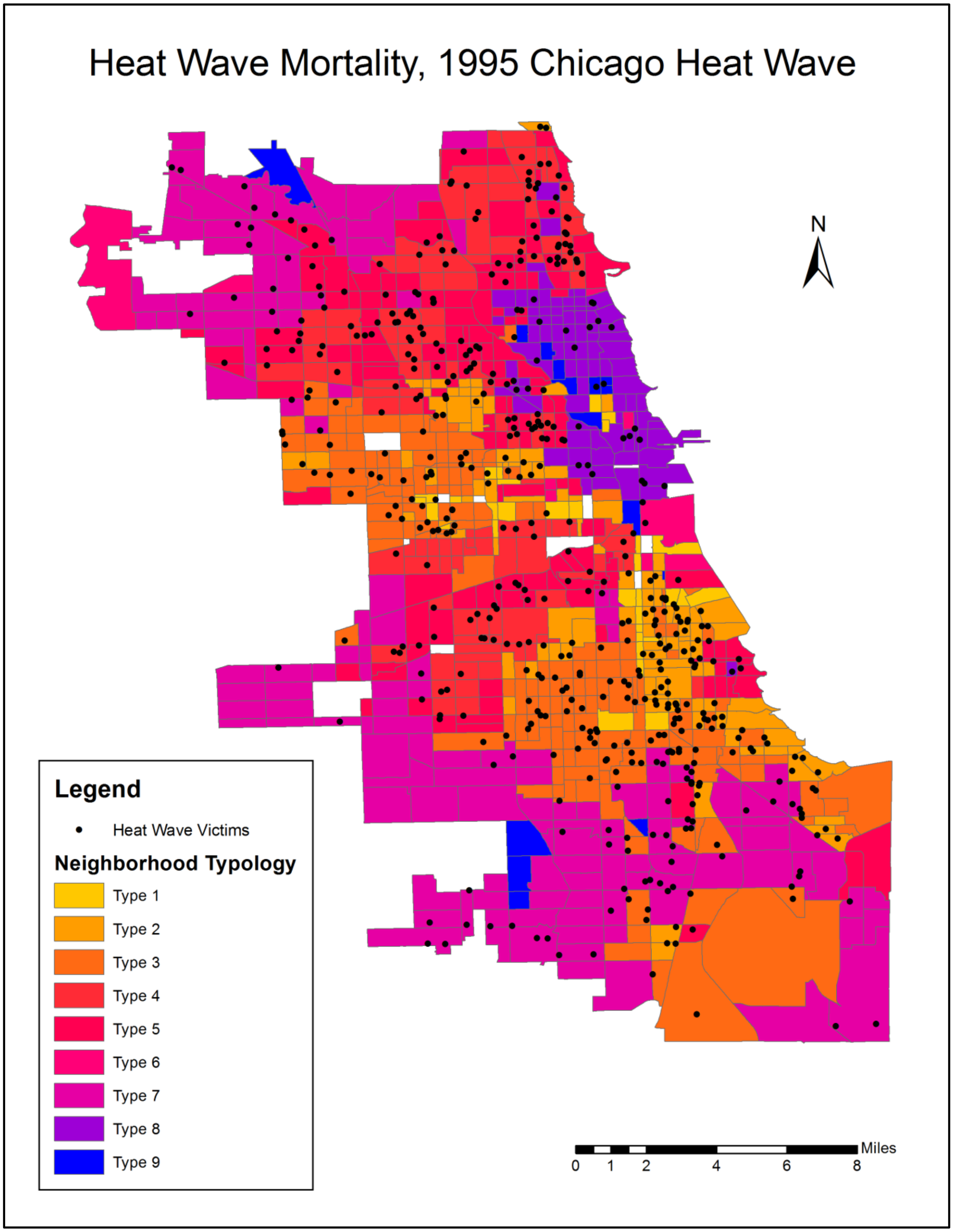
Spatial Visualization

Figure 2 provides an overview of the distribution of heat wave-related deaths within census tracts in Chicago with identified neighborhood typologies. Upon initial observation, Figure 2 indicates a general relationship between mortality during the 1995 Chicago Heat Wave and neighborhood types in Chicago. A subsection of neighborhood types, specifically census tracts classified as Type 6 or greater, appear to experience zero or relatively few heat wave-related deaths.

Graphical Visualizations

As demonstrated in Figure 3, more detailed analyses of the distribution of heat wave victims provide several illuminating points. First, the distribution of victims per census tracts is extremely asymmetrical, and in fact is skewed to the right. Of the 850 census tracts in Chicago considered, a majority of them experienced zero heat wave mortalities. Specifically, 507 census tracts (approximately 60%) did not have any heat wave deaths attributed to them. Of the 343 census tracts that did contain mortalities, approximately 61% of them experienced one death and 28% of them experienced two deaths. The remaining 11% experienced between three and six deaths. No single census tract experienced seven or more heat wave-related deaths.

Additionally, detailed profiles of census tracts by the degree of mortality experienced provides evidence to indicate a relationship between neighborhood typology and mortality. To begin with, Type 9 census tracts never experienced more than one heat wave-related death. Furthermore, the proportion of census tracts Type 6 or greater decreases as the mortality per census tract increases. This trend validates the observation that census tracts classified as Type 6 or greater may experience fewer heat wave-related deaths from Figure 2. Statistical analyses are needed to determine the validity of this observation, and perhaps reveal minute trends not visible in Figures 2 and 3.



Sources: DNT Neighborhood Typology (2000), *Heat Wave: An Oral History* (2015), U.S. Census TIGER/Line Shapefile (2000)

Figure 2: Overview Map of Mortality and Neighborhood Typology in Chicago

Sources: DNT Neighborhood Typology (2000), *Heat Wave: An Oral History* (2015), U.S. Census TIGER/Line Shapefile (2000)

Figure 3: Detailed Summary of Victim Distribution

Statistical Regressions

Individual Neighborhood Types

STATA regression analyses were conducted to determine the degree to which individual neighborhood types function as predictors of heat wave mortality. Dummy variables were generated for each neighborhood type. Individual regressions were run for each neighborhood type, with their respective dummy variables serving as the independent variable and the number of deaths serving as the dependent variable. See Appendix 4 for complete STATA outputs of regression analyses for individual neighborhood types.

Figure 4 summarizes the results of regression analyses conducted for individual neighborhood types. Six of nine neighborhood types were found to be significant predictors of heat wave mortality. Type 1, Type 2, Type 4, and Type 8 classifications were found to be significant at the 0.05 level. Meanwhile, Type 3 and Type 9 classifications were found to be significant at the 0.10 level. Furthermore, the coefficients for dummy variables representing neighborhood types indicate there is some validity to the previous observation that higher neighborhood types are associated with relatively lower rates of mortality. As Figure 4 demonstrates, a majority of coefficients for Types 1 – 4 are positive, while all of the coefficients for Types 5-9 are negative.

In having a negative coefficient, Type 1 neighborhoods deviate from the general trend of positive coefficients demonstrated among low-tier neighborhood types (Types 1-4). This deviation may be due to the fact that a small number of census tracts (32), are classified as Type 1. Meanwhile, Types 2-4 have at least 100 census tracts that are classified as each neighborhood type. The relatively small sample size for Type 1 neighborhoods may have made the neighborhood type more susceptible to extreme outliers not representative of most Type 1 neighborhoods.

Neighborhood Type	Constant	Coefficient	p-value
1	0.647	-0.365	0.032 *
2	0.595	0.309	0.002 *
3	0.605	0.135	0.090 **
4	0.592	0.285	0.002 *
5	0.655	-0.123	0.145
6	0.637	-0.415	0.190
7	0.657	-0.136	0.111
8	0.664	-0.293	0.006 *
9	0.641	-0.441	0.074 **

* Significant at the 0.05 level
** Significant at the 0.10 level

Figure 4: Summary of Regression Analyses - Individual Neighborhood Types

Because of the way that dummy variables for each neighborhood type were defined, a positive coefficient indicates that the group of census tracts classified as the neighborhood type of interest are associated with a higher number of deaths than the group of census tracts classified as other neighborhood types. Conversely, a negative coefficient indicates that the group of census tracts classified as the neighborhood type of interest are associated with a lower number of deaths than the group of census tracts classified as other neighborhood types.

For example, the regression analysis conducted for Type 1 can be interpreted as follows:

Because $Type$ 1 is a dummy binary variable, it has the following values:

$Type\ 1 = 0$: Census tract is not classified as Type 1
$Type\ 1 = 1$: Census tract is classified as Type 1

The estimating equation for the model is:

$$Heat\ \widehat{Wave}\ Deaths = 0.647 - 0.365 * Type\ 1$$

Because the p-value for the Type 1 variable is 0.032, the model is significant at the 0.05 level. Thus, there is a significant relationship between neighborhood type and mortality. Census tracts classified as Type 1 are associated with a decrease in heat wave-related deaths of about 0.365 when compared to census tracts classified as Types 2-9. (See Appendix 4 for complete STATA outputs used to inform estimating equations and model interpretations.)

Low vs. High-Tier Neighborhood Types

The previous observation that higher neighborhood types are associated with lower rates of mortality is further supported by the results of STATA regression analyses that categorize census tracts into low-tier and high-tier groups. Dummy variables were generated for the group of census tracts classified as high-tier neighborhood types. A high-tier group was defined using two methods, and thus two regression analyses were run. Both regression analyses considered the high-tier dummy variable as the independent variable and the number of deaths as the dependent variable. See Appendix 5 for complete STATA outputs of regression analyses for low and high-tier groups.

Figure 5 summarizes the results of regression analyses conducted for high-tier groups. The first regression analysis defined a high-tier group as being composed of census tracts classified as Types 5-9. This definition corresponds with findings from previous regression analyses of individual neighborhood types, summarized in Figure 4, in which all coefficients for Types 5 and above were negative. Alternately, the second regression analysis defined a high-tier group as being composed of census tracts classified as Types 6-9. This definition is narrower than the first, and was used for comparative purposes.

Low-Tier Group	High-Tier Group	Constant	Coefficient	p-value
Types 1-4	Types 5-9	0.784	-0.309	0.000 *
Types 1-5	Types 6-9	0.718	-0.278	0.000 *

* Significant at the 0.05 level

Figure 5: Summary of Regression Analyses – Low vs. High-Tier Groups

In both regression analyses, a high-tier neighborhood type was found to be a significant predictor of heat wave mortality. According to both definitions, a high-tier neighborhood type was significant at the 0.05 level. When the high-tier group is defined as Types 5-9, high-tier census tracts are associated with a decrease in heat wave-related deaths of about 0.309 when compared to low-tier census tracts. Alternately, when the high-tier group is defined as Types 6-9, high-tier census tracts are associated with a decrease in deaths of about 0.278 when compared to low-tier tracts. The first definition of a high-tier group, which only considers Types 5-9, demonstrates the largest reductive effect on mortality because its associated coefficient has the higher absolute value.

Low-Tier Neighborhood Types

Regression analyses reveal few distinctions between neighborhood types in the low-tier group. For the purposes of these analyses, low-tier neighborhood types were considered census tracts classified as Type 5 and lower. Type 1 neighborhoods were excluded from this analysis because their effect on mortality deviated from the broader trend of increased mortality demonstrated among low-tier neighborhood types. As seen in Figure 4, the Type 1 variable has a negative coefficient, which indicates Type 1 neighborhoods are associated with a decrease in the number of heat wave-related deaths when compared to other neighborhood types. Dummy variables were generated for a range of scenarios with different low-tier reference and non-reference groups. A total of six regression analyses were run in order to compare every low-tier neighborhood type against every other low-tier neighborhood type. Regression analyses considered the low-tier dummy variable as the independent variable and the number of deaths as the dependent variable. See Appendix 6 for complete STATA outputs of regression analyses for low-tier neighborhood types.

Figure 6 summarizes the results of regression analyses conducted for low-tier neighborhood types. A single neighborhood type, Type 5, was found to be a significant predictor of heat wave mortality. In all of its three regression analyses, Type 5 was found to be significant at the 0.05 level. Additionally, the regression analyses produced negative coefficients for the dummy variable representing Type 5 classification. In other words, census tracts classified as Type 5 are associated with lower rates of heat wave mortality when compared to all other low-tier neighborhood types.

Reference Group	Non-Reference Group	Constant	Coefficient	p-value
Type 2	Type 3	0.904	-0.164	0.216
Type 2	Type 4	0.904	-0.027	0.861
Type 2	Type 5	0.904	-0.371	0.004 *
Type 3	Type 4	0.740	0.137	0.258
Type 3	Type 5	0.740	-0.208	0.040 *
Type 4	Type 5	0.877	-0.345	0.003 *

* Significant at the 0.05 level

Figure 6: Summary of Regression Analyses – Low-Tier Group

The regression analyses conducted for Type 5 can be interpreted as follows:

- Census tracts classified as Type 5 are associated with a decrease in heat wave-related deaths of about 0.371 when compared to census tracts classified as Type 2.

- Census tracts classified as Type 5 are associated with a decrease in heat wave-related deaths of about 0.208 when compared to census tracts classified as Type 3.

- Census tracts classified as Type 5 are associated with a decrease in heat wave-related deaths of about 0.345 when compared to census tracts classified as Type 4.

Ultimately, regression analyses of low-tier neighborhood types provide consistent evidence that only census tracts classified as Type 5 are associated with significantly lower rates of mortality among low-tier neighborhood types. The implications of this conclusion are important. Stated in other terms, this finding reveals that there are no discernable differences between low-tier neighborhood types in terms of their effects on heat wave mortality, with the exception of Type 5. Furthermore, if the primary definition of low-tier neighborhood types, which consists of Types 1-4, was utilized in this analyses, the conclusion would be even more simple: In terms of heat wave mortality, there is no significant difference in predictive effect between low-tier neighborhood types.

Discussion of Mortality Risk Analysis

Relationship Between Neighborhood Type and Heat Vulnerability

A series of regression analyses validated initial observations made from spatial and graphical visualizations of heat wave mortality during the 1995 Chicago Heat Wave. The results of individual regression analyses for neighborhood types indicated that higher neighborhood types are associated with lower rates of mortality. As demonstrated in Figure 4, a majority of coefficients for Type 1-4 were found to be positive, while all the coefficients for Types 5-9 were found to be negative. Additional regression analyses that evaluated differences in mortality between low-tier and high-tier neighborhoods provided further evidence to support this broader trend. Classification as a high-tier neighborhood type was found to be a significant predictor of heat wave mortality. As Figure 5 demonstrates, when a high-tier group is defined as Types 1-4, high-tier census tracts are associated with a decrease in heat wave-related deaths of about 0.309 when compared to low-tier census tracts.

While a broad relationship between neighborhood types and heat wave mortality was established, further regression analyses revealed few differences between low-tier neighborhood types with regards to their predictive power. A single neighborhood type, Type 5, was found to be a significant predictor of heat wave mortality. As Figure 6 demonstrates, census tracts classified as Type 5 are associated with a decrease in heat wave-related deaths of at least 0.208 when compared to every low-tier neighborhood type. However, it is important to note that this conclusion results from the use of a more inclusive definition of a low-tier group to designate reference and non-reference groups. If a high-tier group was defined as being comprised of Types 5-9, which Figure 5 demonstrates has the greatest reductive effect on mortality, Type 5 would not be considered a low-tier neighborhood type. Thus, it is not unreasonable to define a low-tier group as Types 1-4 and subsequently conclude that there is no significant difference in predictive effect between low-tier neighborhood types.

Tradeoffs Between Heat Risk Reduction and Displacement

Findings from the analysis of heat mortality attributed to the 1995 Chicago Heat Wave offer a cautionary tale when considering the use of neighborhood economic development as a tool for hazard mitigation. Interventions to induce changes in neighborhood type can pose tradeoffs between reducing the risk of heat-related mortalities and displacing existing residents, particularly in low-income neighborhoods.

Figure 7 outlines changes in heat-related mortality risk and average household income associated with the transition of a Type 2 neighborhood. According to the *Dynamic Neighborhoods* final report, low-income communities tend to change neighborhood types more often than high-income communities. Type 2 neighborhoods are no exception, and are in fact particularly unstable. Only about

46% of existing Type 2 neighborhoods remained unchanged during the 10-year period between 1990 and 2000 (Weissbourd, Bodini, and He 2009). As Appendix 8 demonstrates, Type 2 neighborhoods are most likely to transition into Type 3, Type 4, Type 5, Type 6, or Type 8 neighborhoods. Two additional regression analyses were conducted to compare Type 2 neighborhoods against the five neighborhood types it was most likely to transition into. Dummy variables were generated for the two additional scenarios with different non-reference groups (Type 6 and Type 8). Regression analyses considered the dummy variable as the independent variable and the number of deaths as the dependent variable. See Appendix 7 for complete STATA outputs of these regression analyses.

Reference Group	Non-Reference Group	Coefficient	p-value	Change in Average Household Income
Type 2	Type 3	-0.164	0.216	2,900
Type 2	Type 4	-0.027	0.861	11,100
Type 2	Type 5	-0.371	0.004 *	16,400
Type 2	Type 6	-0.682	0.097 **	19,100
Type 2	Type 8	-0.533	0.000 *	31,100

* Significant at the 0.05 level
** Significant at the 0.10 level

Source: *Dynamic Neighborhoods: New Tools for Community and Economic Development* (pages 121-143)

Figure 7: Summary of Regression Analyses – Tradeoffs of Neighborhood Change

As Figure 7 demonstrates, a radical transition in neighborhood type is needed for a Type 2 community to experience a significant reduction of mortality risk due to neighborhood change. A Type 2 community would only be likely to experience a significant reduction in heat wave mortality if it transitioned into a Type 5, Type 6, or Type 8 neighborhood. This is the case because regression analyses only indicate Type 5, Type 6, and Type 8 neighborhoods are associated with a significant decrease in the number of heat-related deaths compared to Type 2 neighborhoods at the 0.10 level.

However, Type 2 communities that transition into higher income neighborhood types may face displacement of low-income renters due to rising housing costs. Median incomes in Type 2 neighborhoods average around $20,900 (Weissbourd, Bodini, and He 2009). As Figure 7 demonstrates, significant reductions in heat vulnerability for a transitioning Type 2 neighborhood will be associated with an increase in average household income of *at least* $16,400—almost 80% of its initial average income. Unfortunately, there is no scenario where a Type 2 neighborhood can transition in a manner that is associated with both a significant reduction in heat vulnerability *and* minimal displacement. Ultimately, caution should be exercised when advocating for economic development as a strategy for reducing heat vulnerability to avoid displacing vulnerable low-income residents in the name of hazard mitigation.

Policy Recommendations

Findings from an analysis of mortalities attributed to the 1995 Chicago Heat Wave established a general relationship between neighborhood typology and heat vulnerability, with some limitations. By communicating neighborhood dynamics in an intuitive manner, neighborhood typologies can serve as an "actionable" data-based reference for policymakers engaged in emergency management and hazard mitigation planning. The following recommendations outline a range of actions policymakers can adopt to improve the performance of emergency management and hazard mitigation strategies for future heat events within the City of Chicago.

Recommendation #1: *Develop neighborhood-specific heat response plans to effectively address intra-city variations in heat vulnerability.*

Analysis of mortality data from the 1995 Chicago Heat Wave provided evidence affirming a broad relationship between neighborhood type and heat vulnerability within the city. Results from a series of regression analyses indicate that high-tier neighborhood types are associated with significantly lower rates of mortality than those found in low-tier neighborhood types. Given these pronounced community-level differences in heat vulnerability, policymakers should utilize the most recent 2006 DNT typology to inform the development of heat response plans for specific neighborhoods. In doing so, policymakers can effectively allocate limited municipal resources in accordance with the unique assets, needs, and constraints of individual communities. More specifically, the DNT typology can facilitate heat event preparedness and real time decision-making by presenting information regarding relevant demographic and built environment characteristics to policymakers, including the availability of civic or private places for heat relief and educational or linguistic barriers to disseminating public health information to residents.

Recommendation #2: *Integrate neighborhood "greening" initiatives with local land use planning process to promote the implementation of high-impact heat mitigation projects.*

As previously stated, analysis of mortality data from the 1995 Chicago Heat Wave indicates low-tier neighborhood types are associated with significantly higher rates of heat vulnerability than their high-tier counterparts. Neighborhoods that experience a relatively high degree of heat vulnerability due to place-based factors, specifically a high proportion of impervious land cover and/or lack of vegetation, are ideal candidates for greening initiatives that aim to moderate urban heat island effects at the community-scale. In coordination with local planning agencies, policymakers should use the 2006 DNT typology to identify neighborhoods in Chicago most poised to benefit from greening initiatives, and then incorporate these mitigation strategies into small area and open space/park plans as needed. By engaging in a collaborative process, policymakers can mobilize the resources of multiple public entities, ensure consistency across relevant plans, and avoid executing fragmented projects with limited results. Ultimately, this multi-agency approach will increase the likelihood of implementation and the realization of public health benefits from community-scale greening initiatives.

Recommendation #3: *Use DNT neighborhood trends to anticipate and prepare for changes in intra-city heat vulnerability.*

The *Dynamic Neighborhoods* final report suggests that neighborhoods have a 30% chance of changing type within a 10-year period. However, the likelihood of undergoing a neighborhood transition varies according to neighborhood type, as low-income communities tend to change neighborhood types more often than high-income communities (Weissbourd, Bodini, and He 2009). Given the fluid nature of neighborhood types, policymakers should utilize the DNT Neighborhood Transition Matrix (shown in Appendix 8) to anticipate changes in heat vulnerability due to neighborhood transitions, monitor neighborhoods of interests, and plan future emergency management and land use programs accordingly. For example, policymakers can use the Transition Matrix to identify neighborhoods most likely to transition from high-tier to low-tier neighborhood types and thus experience a significant increase in heat vulnerability. Additionally, policymakers can identify neighborhoods most likely to remain low-tier neighborhood types, which would experience no significant changes in heat vulnerability. Because these neighborhoods are sites of existing and likely continued high rates of heat vulnerability, policymakers should prioritize long-term heat mitigation planning in these communities.

Recommendation #4: *Assess the impact of community-scale programs by using the DNT typology to identify comparable neighborhoods.*

As the *Dynamic Neighborhoods* final report describes, the use of hybrid hierarchical clustering to construct the DNT Neighborhood Typology allows the closest peer of any given neighborhood to be identified (Weissbourd, Bodini, and He 2009). This feature has important implications for impact analyses evaluating the effects of heat-related hazard mitigation projects at the neighborhood level. By identifying neighborhoods comparable to the one or ones in which an intervention is implemented, DNT typology allows a user to establish control or baseline conditions. Thus, changes in indicator variables due to an intervention can be distinguished from those due to broader regional trends. When assessing the impact of neighborhood-scale mitigation projects, policymakers should use the 2006 DNT typology to identify comparable neighborhoods, thus improving the design of impact studies and the quality of its findings. Employing the DNT typology in this manner provides policymakers with opportunities to appropriately evaluate existing or future pilot programs implemented in one or many neighborhoods.

Recommendation #5: *Consider SROs and senior public housing as "hotspots" of heat vulnerability to address vulnerable populations not captured at the neighborhood-level.*

Analysis of mortality data from the 1995 Chicago Heat Wave found no discernable differences between low-tier neighborhood types (Type 1-4) in terms of their effects on heat wave mortality. This conclusion was likely reached because the geographic scale used to evaluate patterns of heat mortality, census tracts, was too large to capture known variations in heat vulnerability within neighborhoods. As Klinenberg contends in *Heat Wave*, a disproportionately high number of deaths attributed to the 1995 Heat Wave may have occurred in single room occupancy (SROs) dwellings and senior public housing (Klinenberg 2002). Given that both of these types of residences tend to house populations with individual risk factors that increase the likelihood of heat-related illness or death, policymakers engaged in emergency management and hazard mitigation should consider SROs and senior public housing facilities as priority sites for interventions. Policymakers should be wary of interpreting the finding that there are no significant differences between low-tier neighborhoods as there being no residential properties that function as points of extreme heat vulnerability within already vulnerable neighborhoods.

Conclusion

Findings from an analysis of deaths attributed to the 1995 Chicago Heat Wave provide evidence to affirm a general relationship between the DNT Neighborhood Typology and heat vulnerability within Chicago. Regression analyses indicate low-tier neighborhood types are associated with a significantly higher heat risks than high-tier neighborhood types. The demonstrated relationship between neighborhood typology and heat vulnerability has several implications for heat-related emergency management and hazard mitigation planning for the City of Chicago. By communicating neighborhood dynamics in an intuitive manner, neighborhood typologies provide an "actionable" data-based reference to facilitate the development of neighborhood-specific heat response and mitigation plans. Additional applications of the DNT typology relevant to policymaking include the use of the tool to anticipate future heat vulnerability and improve the design of impact studies evaluating neighborhood-scale interventions. Ultimately, the unique properties of the DNT Neighborhood Typology provide policymakers with new opportunities to improve the performance of emergency management and hazard mitigation strategies for future heat events in Chicago.

References

CDC. 2001. "Heat-Related Deaths-Los Angeles County, California, 1999-2000, and United States, 1979-1998." http://www.cdc.gov/mmwr/preview/mmwrhtml/mm5029a3.htm.

Chestnut, Lauraine. 1998. "Analysis of Differences in Hot-Weather-Related Mortality Across 44 US Metropolitan Areas." *Environmental Science and Policy* 1 (1): 59–70.

Clarke JF. 1972. Some Effects of the Urban Structure on Heat Mortality. *Environmental Research* 5 (1): 93-104

Johnson, Daniel P. 2012. "Developing an Applied Extreme Heat Vulnerability Index Utilizing Socioeconomic and Environmental Data." *Applied Geography* 35 (1-2): 23-31.

Kilbourne, E. 1982. "Risk Factors for Heatstroke. A Case-Control Study." *JAMA* 247 (24): 3332–36.

Kim, Youngmin, and Seunghun Joh. 2006. "A Vulnerability Study of the Low-Income Elderly in the Context of High Temperature and Mortality in Seoul, Korea." *Science of the Total Environment* 371 (1-3): 82–88.

Klinenberg, Eric. 2002. Heat Wave: *A Social Autopsy of Disaster in Chicago*. Chicago, IL: The University of Chicago Press.

Knowlton, K. 2009. "The 2006 California Heat Wave: Impacts on Hospitalizations and Emergency Department Visits." *Environmental Health Perspectives* 117 (1): 61–67.

Luber, Sanchez. 2006. "Heat-Related Deaths-United States, 1999-2003." *Morbidity and Mortality Weekly Report*. http://www.cdc.gov/mmwr/preview/mmwrhtml/mm5529a2.htm.

Medina-Ramon, M. 2006. "Extreme Temperatures and Mortality: Assessing Effect Modification by Personal Characteristics and Specific Cause of Death in a Multi-City Case-Only Analysis." *Environmental Health Perspectives* 114 (9): 1331–36.

Naughton, M. 2002. "Heat-Related Mortality during a 1999 Heat Wave in Chicago." *American Journal of Preventive Medicine* 22 (4): 221–27.

Reid, Colleen E. 2009. "Mapping Community Determinants of Heat Vulnerability." *Environmental Health Perspectives* 117 (11): 1730–36.

Rosenthal, Joyce K. 2014. "Intra-urban Vulnerability to Heat-related Mortality in

New York City, 1997-2006." *Health and Place* 30: 45-60.

Schwartz, J. 2005. "Who Is Sensitive to Extremes of Temperature? A Case-Only Analysis." *Epidemiology* 16 (1): 67–72.

Stafoggia, Forastiere. 2006. "Vulnerability to Heat-Related Mortality: A Multicity, Population-Based, Case-Crossover Analysis." *Epidemiology* 17 (3): 315–23.

Thomas, Mike. 2015. "An Oral History: Heat Wave." Chicagomag.com. http://www.chicagomag.com/Chicago-Magazine/July-2015/1995-Chicago-heat-wave/.

Uejio, Christopher K. 2011. "Intra-urban Societal Vulnerability to Extreme Heat: The Role of Heat Exposure and the Built Environment, Socioeconomics, and Neighborhood Stability." *Health and Place* 17 (2): 498–507.

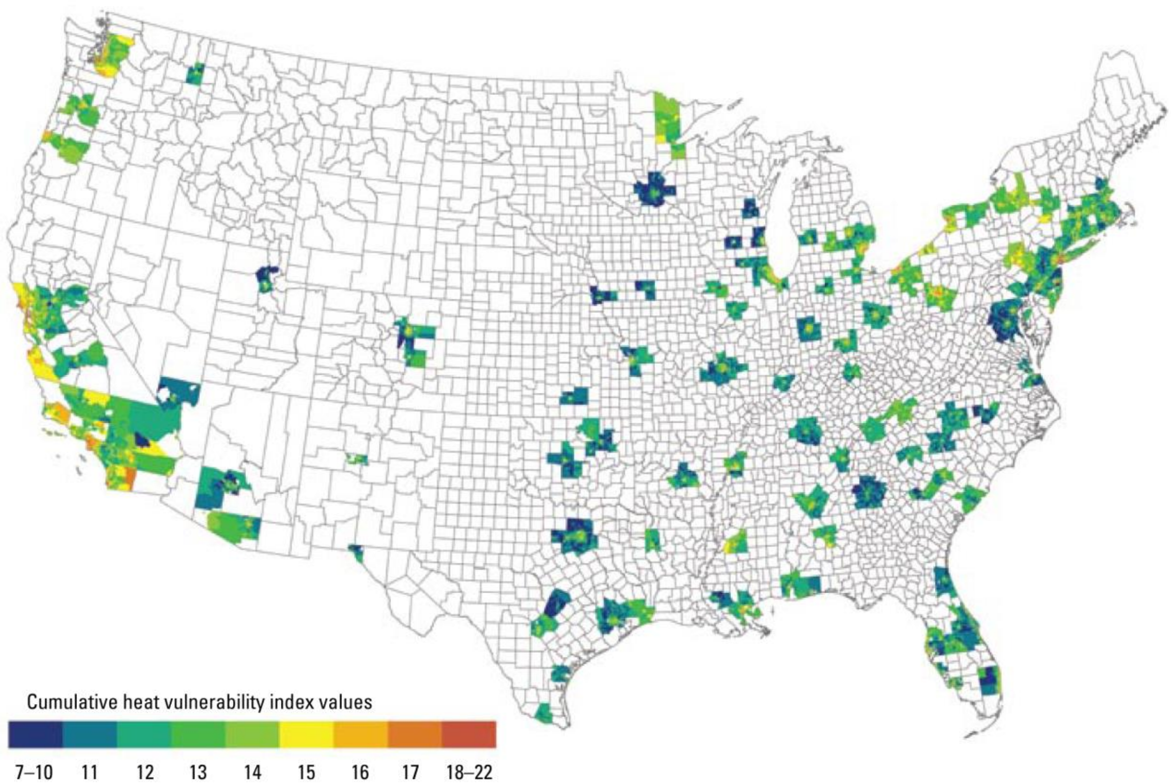
Walk Score. 2016. "Walk Score Methodology." https://www.walkscore.com/methodology.shtml.

Weissbourd, Robert, Riccardo Bodini, and Michael He. 2009. Dynamic Neighborhoods: New Tools for Community and Economic Development. Chicago, IL. http://www.rw-ventures.com/ftp/DNT Final Report.pdf.

Appendix

Appendix 1: Methodology of Heat Vulnerability Index

The Heat Vulnerability Index was composed in 2009 to map national heat vulnerability at the census tract-level. The Index utilized ten variables shown to increase vulnerability to heat-related health effects in urban areas and for which national data sets were available. Variable were grouped into four factors, including social and environmental vulnerability, social isolation, prevalence of no air conditioning, and proportion of elderly and diabetes. The Heat Vulnerability Index summed these four factors and produced cumulative values that ranged from 7 to 22. As the map below illustrates, spatial clustering of heat vulnerability near urban areas occurs throughout the nation.



Source: Reid, Colleen E. 2009. "Mapping Community Determinants of Heat Vulnerability." *Environmental Health Perspectives* 117 (11): 1730–36.

Appendix 2: Profiles of DNT Neighborhood Types

Type 1: The Truly Disadvantaged	
Highlights	Neighborhoods in Type 1 struggle with poverty, crime, and unemployment. Streets lined with vacant lots, public housing projects and industrial infrastructure are the physical realities of these communities; children and their single parents, along with seniors, make up the majority of their population, which is mostly African American. Many residents hold no high school diploma, and unemployment rates are several times higher than the national average. Most residents are employed in service or sales occupations. Businesses and social infrastructure in these neighborhoods are lacking, but their proximity to the city's Central Business District and the presence of developable land create opportunities for reinvestment.
Detailed Profile	This is the poorest of all neighborhood types, with an average median household income of just under $10,000.[15] Moreover, there is very little income diversity: incomes are concentrated in the lower end of the spectrum to a much greater extent than in the other lower income neighborhood types. The population is primarily African American, and composed of children, seniors, and very few adults between the age of 35 and 64. A large percentage of the residents live in public housing. Other socio-economic indicators are consistent with the profile of an economically distressed neighborhood. The mean unemployment rate is 35%, and 49% of adults do not have a high school diploma. On average, about 36% of households are single parent households. Homicide, violent and property crime rates are, on average, the highest among all clusters. A look into the physical characteristics of these neighborhoods reveals indicators of significant disinvestment and distress as well. The percentage of vacant parcels is the highest among all clusters (on average 22% of land parcels are vacant), and only about a third of the parcels are residential. Furthermore, many of the housing units that exist are vacant (average rate is 21%). Business presence is very low, and the diversity of business types is the lowest of all clusters. However, this is one of the most heterogeneous clusters, and individual neighborhoods within it might differ from this description with respect to particular dimensions.

Type 2: Transient Underdeveloped	
Highlights	Moving trucks and vacancy signs exemplify this type of neighborhood. Frequently close to the city center, Type 2 neighborhoods have quick turnover in their residents. Very few people own their homes, and residents tend to live in apartments as opposed to single family housing. Most of the residents are employed, but Type 2 neighborhoods have high crime rates and very little diversity in businesses. Proximity to the city center, low property values and vacant land make this neighborhood cluster susceptible to improvement with some degree of displacement.
Detailed Profile	Neighborhood Type 2 represents a low income segment with high levels of rental housing and resident turnover. Only 18% of households are homeowners, and median incomes average around \$20,900. As in the case of "The Truly Disadvantaged" neighborhood type, incomes are typically concentrated in the lower end of the spectrum. This type includes residents of all age groups and racial identities, but for the most part they tend to sort into different neighborhoods. Socio-economic indicators in general reveal signs of economic and social distress: 20% of residents are unemployed, and 41% of adults do not have a high school diploma. Crime rates are also very high. Type 2 neighborhoods are typically located near the central business district, and have a diverse mix of land uses, with lower than average percentages of residential land, above average vacant land, but also a fair amount of commercial and industrial parcels. Retail and service business diversity, however, remains low.

Type 3: Stable Low Income	
Highlights	Modest, single family homes and well-worn city blocks provide the backdrop to stable communities in Type 3. The residents of these neighborhoods, primarily African American, often own their single family homes and find employment in a wide variety of occupations: a resident is as likely to hold a white collar job as a job in the service sector, in sales, or in a factory. These neighborhoods lack business and service amenities, but their residents get by – even if it is sometimes a struggle on a median income of \$23,800 – and over half of them live in the neighborhood for more than 10 years. High crime and foreclosure rates are two outstanding challenges for this type of neighborhood.
Detailed Profile	Neighborhoods in this segment tend to be lower income communities with relatively high levels of home ownership and resident stability. However, other socioeconomic indicators point to potential difficulties in the residents' lives: unemployment is relatively high at 19%, about 38% of adults do not have a high school diploma, and median income levels are fairly low at \$23,800. Many families find homes within these neighborhoods, but typically 23% of households are led by a single parent. Indicators of financial distress such as balance to credit limit ratios and foreclosure rates are also among the highest of all clusters. These neighborhoods tend to be highly residential, with very little business presence. Many of them also have relatively high concentrations of vacant land. Still, resident stability is very high, as on average, 44% of households have lived in the same home for over ten years.

Type 4: Port of Entry	
Highlights	Blocks animated by a variety of businesses and residents' native languages make up the neighborhoods of Cluster 4. Most of Type 4 neighborhoods have a Hispanic majority, though these communities can also be enclaves of Asian and European immigrants. Almost half of neighborhood residents were born outside the United States, and many are raising families in these parts of the city with little crime and well-used space. Many residents move from their homes—few of which are single-family dwellings—after a few years, but may stay in the neighborhood. Residents have slightly lower-than-average incomes, but unemployment is less than 10%, and two parents are present in most households with children.
Detailed Profile	Neighborhoods in this cluster represent the bulk of the "immigrant communities" in the typology, with 45% of their population being foreign born. Although most of these neighborhoods are primarily Hispanic, there are a few that are majority non-Hispanic White or Asian (particularly in Seattle). Cluster 4 lies on the line between low and moderate income clusters ($32,000 household income on average), but its socioeconomic indicators are more similar to the mid- to higher- income clusters than to the lower income groups. In particular, these neighborhoods are characterized by lower unemployment rates, lower percentages of single parent households, and greater income diversity. Resident mobility is relatively high, consistent with the "port of entry" character of these communities. Employment in these neighborhoods tends to be concentrated in a few specific occupations, more so than in other neighborhood types. About 24% of adults in the labor force are employed in production and transport occupations, and 12% of residents are employed in the construction sector, both of which are the highest rates among all clusters. Conversely, the proportion of residents in professional, sales and office occupations are considerably lower than in the other mid- to high- income clusters. This is consistent with the fact that, on average, 47% of adults do not have a high school diploma. Business presence is among the highest of all clusters. However, the types of businesses that characterize these communities vary greatly within this cluster, with some neighborhoods having a greater presence of local shops, while others have a greater concentration of large business establishments.

Type 5: Urban Tapestry	
Highlights	These neighborhoods tend to be "eclectic" areas that harbor a wide variety of people and businesses. Indeed, the features that define Type 5 neighborhoods are the ethnic diversity of the population —White, Hispanic and, to a lesser extent, African American — and a healthy diversity in business types. Most of the land is residential and little is left vacant. Residents tend to live in older housing and many own their single family homes. Almost half of them have some kind of advanced education and many work in professional occupations.
Detailed Profile	It is not a coincidence that Type 5 falls in the middle of the nine neighborhood groups identified by this typology. In many ways, this group represents a "middle ground" moderate income cluster. While the cluster as a whole does not have any outstanding features that distinguish it from the average, it is home to some of the most diverse neighborhoods in the city. In a few instances, this cluster also includes census tracts that have very distinct and different areas within their boundaries, separated by barriers such as hills, rivers or freeways. The average household income is $37,300, which is close to the average across all neighborhood types. Racial diversity is among the highest across all clusters, although there are significant differences between the individual sub-types. Unemployment rates are low, and about 50% of adults have either a BA or advanced degrees. Crime rates are also relatively low. Neighborhoods in this cluster are usually located mid-way between downtown and the city limits. Most of the neighborhoods are built out, with a moderate proportion of single family homes and moderate amounts of business concentration. At the same time, existing housing structures are among the oldest in the city.

Type 6: Coming Attractions	
Highlights	Usually built within the last 20 years, the neighborhoods in Cluster 6 attract a racially diverse mix of residents between the ages of 19 and 34, for the most part employed in professional occupations. These neighborhoods are typically further from the Central Business District and most residents have lived in them for less than 5 years. Median incomes are just under $40,000, but highly diverse businesses pop up and stay in the neighborhoods, providing services and entertainment for the residents.
Detailed Profile	Neighborhoods in this cluster can be characterized as "new developments." The average age of the housing stock in these neighborhoods, which are located primarily in Dallas and Seattle, is only 19 years. At the same time, business presence within these newer communities is fairly high, and the diversity of business types is among the highest among all clusters. The types of housing and overall levels of business presence, however, can vary greatly within this group. The population in these neighborhoods is typically characterized by a high percentage of young adults and a low percentage of children. Incomes are moderate, but residents tend to be well educated, as 70% have at least a high school diploma. About 95% of the work force is employed, with 53% holding professional occupations. Racial diversity is also relatively high across most of these neighborhoods.

Type 7: No Place Like Home	
Highlights	Characterized by a distinct "suburban" feel, neighborhoods in Type 7 are populated with single family homes close to the city limits. While these communities are far from being huge estates and white-picket-fence suburbs, city residents of Type 7 live their lives comfortably on moderate to high incomes, and enjoy low crime rates. A nearly equal spread across age groups points to parents raising families in these neighborhoods, and even some retirees staying there after their nests are empty. However, residents probably go elsewhere for shopping and entertainment: "No Place like Home" neighborhoods are mostly residential, with very low concentrations and diversity of retail and services. In fact, these appear to be stable bedroom communities, as most residents have stayed in the same house for 10 years or more.
Detailed Profile	Neighborhoods in Type 7 tend to be located further away from the central business district, and are characterized primarily by their high home ownership rates (69% of households own their home) and large share of single-family homes (71% of the housing stock is composed of single family detached units). A diverse resident base inhabits these highly residential communities. While the average median income is $45,000 overall, there is a high degree of variation, as median incomes in the neighborhoods that make up this cluster range from the low $30,000s to the upper $50,000s. Racial composition varies as well, although not all neighborhoods within this group are racially diverse. This is a fairly heterogeneous group in terms of age: some communities have more families with children and some have more senior residents. Overall, however, all age groups are represented within these neighborhoods. These neighborhoods are remarkably stable, with an average of 48% of residents who have lived in the same home for over ten years - the lowest turnover rate among all clusters. The majority of Type 7 neighborhoods are built out, have high residential land use and relatively low business presence. While a small portion of neighborhoods in this cluster are recent developments, most neighborhoods tend to have an older housing stock. The key challenge faced by these communities is foreclosures, as they have the second highest foreclosure rates of all clusters.

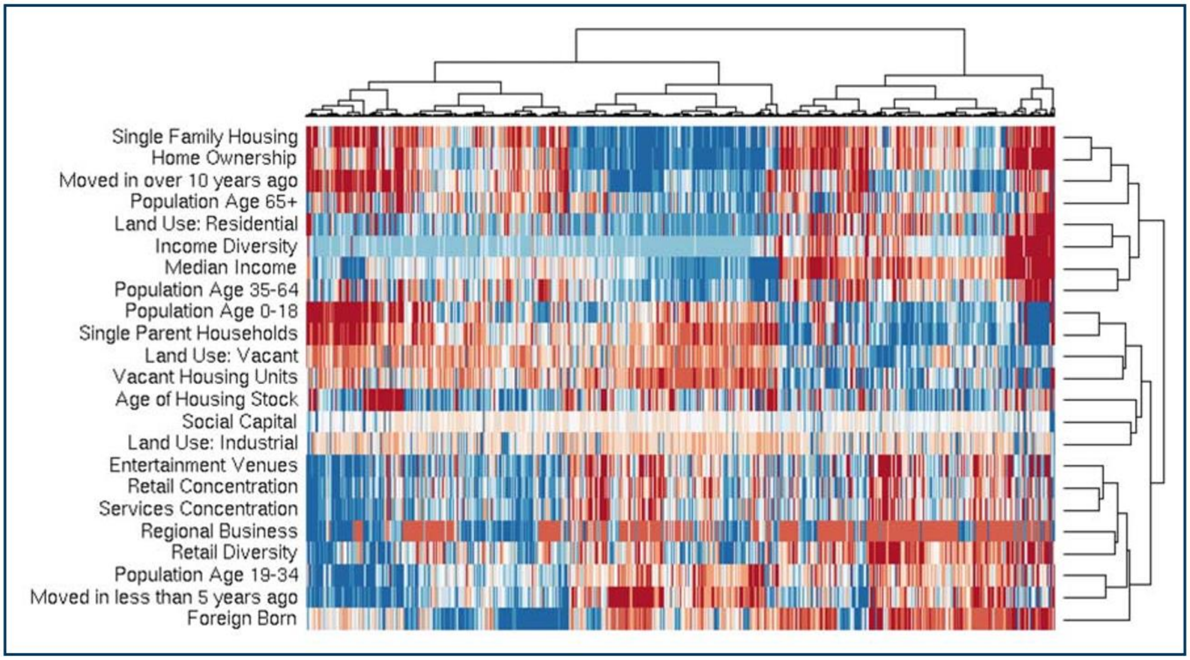
Type 8: Close, Cool and Commercial	
Highlights	Young professionals in these neighborhoods come home to their rented, high-end apartments close to the central business district. Few children frequent the streets in these communities, but the population of 19-34-year-olds enjoys a high diversity and concentration of service, retail, and entertainment businesses. These neighborhoods are not especially diverse in either race or earnings. Almost all residents have some kind of post-high school education, and most work in professional occupations. Few people own their homes, and though these neighborhoods are attractive in both location and amenities, less than a quarter of the population has stayed in them for more than 10 years.
Detailed Profile	Type 8 broadly represents the "young professional" (some might say "yuppie") neighborhoods: on average, 48% of residents are between the ages of 19 and 34, and children make up less than 10% of the population. This highly mobile resident base is also highly educated, and 67% of adults work in professional occupations. Median incomes are, for the most part, moderate to high, and the average level for all neighborhoods in the cluster is $52,000. These neighborhoods are usually majority White and racial diversity is low. Many of these neighborhoods are located near downtown, and, in fact, include downtown areas as well. These are very dense communities, with very few vacancies, and typically have the highest levels of consumption amenities and social capital across all clusters. The majority of housing units are rental, but pockets of single family detached housing are also present.

Type 9: Fortune 100	
Highlights	This type is characterized by expensive single family homes, wealthy homeowners and few business enterprises. With a median income around $100,000, residents of these neighborhoods are mostly professionals with advanced degrees. Low crime rates and long term residential stability make these neighborhoods exclusive and desirable to those who can afford to live in them. The exclusivity of these areas is also evident in the lack of diversity it creates: over 80% of the residents are white and there is little income diversity.
Detailed Profile	This type includes some of the wealthiest neighborhoods in the city, with a median household income of $100,000. Residents of these neighborhoods tend to be older: typically, 45% of residents are between age 35 and 64 (the highest concentration of all clusters), while only 18% are between age 19 and 34 (the lowest concentration of all clusters). These neighborhoods are also home to many families with children, as 23% of the population is less than 18 years old. Socio-economic indicators are, not surprisingly, very positive. Educational attainment is the highest among all clusters, and the unemployment rate is only 3%, lowest among all clusters. Credit indicators such as ratio of balance to credit limit and foreclosure rates are the lowest among all clusters. Residents are mostly employed in white collar jobs, as 71% work in professional occupations. About 77% of households are homeowners, and 74% of housing units are single family detached, both highest among all clusters. Variation in housing type exists across these neighborhoods, however, as some communities tend to be located closer to the central business district and have more rental housing and a greater amount of consumption amenities, while others are located further away from the central city, are more built out, and have an older housing stock.

Source: Weissbourd, Robert, Riccardo Bodini, and Michael He. 2009. Dynamic Neighborhoods: New Tools for Community and Economic Development. Chicago, IL. http://www.rw-ventures.com/ftp/DNT Final Report.pdf.

Appendix 3: Heat Map of the DNT Neighborhood Typology Structure

The heat map below illustrates the overall structure of the DNT neighborhood typology. Neighborhoods are grouped according to their scores on 23 different variables identified as key determinants of neighborhood type. Each column of the heat map can be interpreted as a census tract, and each row represents an indicator variable. The score of each tract is represented by degrees of color, with dark red indicating a very low score and dark blue indicating a very high score.



Source: Weissbourd, Robert, Riccardo Bodini, and Michael He. 2009. Dynamic Neighborhoods: New Tools for Community and Economic Development. Chicago, IL. http://www.rw-ventures.com/ftp/DNT Final Report.pdf.

Appendix 4: STATA Outputs – Regressions of Individual Neighborhood Types

```
. regress Sum_Count clus1_dum

      Source |       SS       df       MS              Number of obs =     850
-------------+------------------------------           F(  1,   848) =    4.62
       Model |  4.11280904     1  4.11280904           Prob > F      =  0.0319
    Residual |  755.364838   848  .890760422           R-squared     =  0.0054
-------------+------------------------------           Adj R-squared =  0.0042
       Total |  759.477647   849  .894555532           Root MSE      =   .9438

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus1_dum |  -.3654493   .1700741    -2.15   0.032    -.6992649   -.0316336
       _cons |   .6466993   .0329992    19.60   0.000     .5819295     .711469
------------------------------------------------------------------------------

. regress Sum_Count clus2_dum

      Source |       SS       df       MS              Number of obs =     850
-------------+------------------------------           F(  1,   848) =    9.82
       Model |  8.69655817     1  8.69655817           Prob > F      =  0.0018
    Residual |  750.781089   848  .885355058           R-squared     =  0.0115
-------------+------------------------------           Adj R-squared =  0.0103
       Total |  759.477647   849  .894555532           Root MSE      =  .94093

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus2_dum |   .3086719   .0984877     3.13   0.002     .1153636    .5019802
       _cons |   .5951743     .03445    17.28   0.000      .527557    .6627915
------------------------------------------------------------------------------

. regress Sum_Count clus3_dum

      Source |       SS       df       MS              Number of obs =     850
-------------+------------------------------           F(  1,   848) =    2.88
       Model |  2.56766477     1  2.56766477           Prob > F      =  0.0902
    Residual |  756.909982   848  .892582526           R-squared     =  0.0034
-------------+------------------------------           Adj R-squared =  0.0022
       Total |  759.477647   849  .894555532           Root MSE      =  .94477

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus3_dum |   .1353582   .0798067     1.70   0.090    -.0212837        .292
       _cons |   .6047548    .036418    16.61   0.000     .5332747    .6762349
------------------------------------------------------------------------------

. regress Sum_Count clus4_dum

      Source |       SS       df       MS              Number of obs =     850
-------------+------------------------------           F(  1,   848) =    9.58
       Model |  8.48811815     1  8.48811815           Prob > F      =  0.0020
    Residual |  750.989529   848   .88560086           R-squared     =  0.0112
-------------+------------------------------           Adj R-squared =  0.0100
       Total |  759.477647   849  .894555532           Root MSE      =  .94106

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus4_dum |   .2850162   .0920625     3.10   0.002     .1043191    .4657133
       _cons |    .592033   .0348781    16.97   0.000     .5235754    .6604906
------------------------------------------------------------------------------
```

```
. regress Sum_Count clus5_dum

      Source |       SS       df       MS              Number of obs =     850
-------------+------------------------------           F(  1,   848) =    2.13
       Model |  1.89860541     1  1.89860541           Prob > F      =  0.1453
    Residual |  757.579042   848  .893371511           R-squared     =  0.0025
-------------+------------------------------           Adj R-squared =  0.0013
       Total |  759.477647   849  .894555532           Root MSE      =  .94518

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus5_dum |  -.1227049   .0841706    -1.46   0.145    -.2879121    .0425023
       _cons |   .6551724   .0358271    18.29   0.000     .5848523    .7254926
------------------------------------------------------------------------------

. regress Sum_Count clus6_dum

      Source |       SS       df       MS              Number of obs =     850
-------------+------------------------------           F(  1,   848) =    1.72
       Model |  1.53445773     1  1.53445773           Prob > F      =  0.1905
    Residual |  757.943189   848  .893800931           R-squared     =  0.0020
-------------+------------------------------           Adj R-squared =  0.0008
       Total |  759.477647   849  .894555532           Root MSE      =  .94541

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus6_dum |  -.4151143   .3168186    -1.31   0.190    -1.036955    .2067262
       _cons |   .6373365   .0326004    19.55   0.000     .5733496    .7013234
------------------------------------------------------------------------------

. regress Sum_Count clus7_dum

      Source |       SS       df       MS              Number of obs =     850
-------------+------------------------------           F(  1,   848) =    2.55
       Model |  2.27492511     1  2.27492511           Prob > F      =  0.1108
    Residual |  757.202722   848  .892927738           R-squared     =  0.0030
-------------+------------------------------           Adj R-squared =  0.0018
       Total |  759.477647   849  .894555532           Root MSE      =  .94495

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus7_dum |  -.1364249   .0854709    -1.60   0.111    -.3041842    .0313344
       _cons |   .6566952   .0356648    18.41   0.000     .5866936    .7266968
------------------------------------------------------------------------------

. regress Sum_Count clus8_dum

      Source |       SS       df       MS              Number of obs =     850
-------------+------------------------------           F(  1,   848) =    7.70
       Model |  6.83186756     1  6.83186756           Prob > F      =  0.0057
    Residual |   752.64578   848  .887553985           R-squared     =  0.0090
-------------+------------------------------           Adj R-squared =  0.0078
       Total |  759.477647   849  .894555532           Root MSE      =   .9421

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus8_dum |   -.292814   .1055406    -2.77   0.006    -.4999654   -.0856626
       _cons |   .6636005   .0341511    19.43   0.000     .5965699    .7306312
------------------------------------------------------------------------------
```

```
. regress Sum_Count clus9_dum

      Source |       SS       df       MS              Number of obs =     850
-------------+------------------------------           F(  1,   848) =    3.21
       Model |  2.8620782     1  2.8620782           Prob > F      =  0.0736
    Residual | 756.615569   848 .892235341           R-squared     =  0.0038
-------------+------------------------------           Adj R-squared =  0.0026
       Total | 759.477647   849 .894555532           Root MSE      =  .94458

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus9_dum |  -.4407186   .2460709    -1.79   0.074    -.9236981    .0422609
       _cons |   .6407186   .0326886    19.60   0.000     .5765585    .7048786
------------------------------------------------------------------------------
```

Appendix 5: STATA Outputs – Regressions of Low and High-Tier Groups

```
. regress Sum_Count high_dum56789

      Source |       SS       df       MS              Number of obs =     850
-------------+------------------------------           F(  1,   848) =   23.30
       Model |  20.3059534     1  20.3059534           Prob > F      =  0.0000
    Residual |  739.171694   848  .871664733           R-squared     =  0.0267
-------------+------------------------------           Adj R-squared =  0.0256
       Total |  759.477647   849  .894555532           Root MSE      =  .93363

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
high_dum56789 |  -.3092093   .0640642    -4.83   0.000    -.4349523   -.1834662
       _cons |    .783908   .0447641    17.51   0.000     .6960466    .8717695
------------------------------------------------------------------------------

. regress Sum_Count high_dum6789

      Source |       SS       df       MS              Number of obs =     850
-------------+------------------------------           F(  1,   848) =   15.85
       Model |  13.9325254     1  13.9325254           Prob > F      =  0.0001
    Residual |  745.545122   848  .879180568           R-squared     =  0.0183
-------------+------------------------------           Adj R-squared =  0.0172
       Total |  759.477647   849  .894555532           Root MSE      =  .93765

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
high_dum6789 |  -.2775534   .0697221    -3.98   0.000    -.4144015   -.1407052
       _cons |   .7181664    .038635    18.59   0.000     .6423349    .7939979
------------------------------------------------------------------------------
```

Appendix 6: STATA Outputs – Regressions of Low-Tier Group

Reference Group: Type 2

```
. regress Sum_Count clus3_dum

      Source |       SS           df       MS      Number of obs   =       281
-------------+----------------------------------   F(1, 279)       =      1.54
       Model |  1.75619837         1  1.75619837   Prob > F        =    0.2163
    Residual |  319.083659       279  1.14366903   R-squared       =    0.0055
-------------+----------------------------------   Adj R-squared   =    0.0019
       Total |  320.839858       280  1.14585663   Root MSE        =    1.0694

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus3_dum |  -.1637332   .1321296    -1.24   0.216    -.4238306    .0963643
       _cons |   .9038462   .1048657     8.62   0.000     .6974177    1.110275
------------------------------------------------------------------------------

. regress Sum_Count clus4_dum

      Source |       SS           df       MS      Number of obs   =       226
-------------+----------------------------------   F(1, 224)       =      0.03
       Model |  .040314031         1  .040314031   Prob > F        =    0.8606
    Residual |  292.194199       224  1.30443839   R-squared       =    0.0001
-------------+----------------------------------   Adj R-squared   =   -0.0043
       Total |  292.234513       225  1.29882006   Root MSE        =    1.1421

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus4_dum |   -.026797   .1524296    -0.18   0.861    -.3271765    .2735825
       _cons |   .9038462   .1119941     8.07   0.000     .6831494    1.124543
------------------------------------------------------------------------------

. regress Sum_Count clus5_dum

      Source |       SS           df       MS      Number of obs   =       258
-------------+----------------------------------   F(1, 256)       =      8.65
       Model |  8.56186062         1  8.56186062   Prob > F        =    0.0036
    Residual |  253.376124       256  .989750484   R-squared       =    0.0327
-------------+----------------------------------   Adj R-squared   =    0.0289
       Total |  261.937984       257  1.01921395   Root MSE        =    .99486

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus5_dum |  -.3713786   .1262687    -2.94   0.004    -.6200363    -.122721
       _cons |   .9038462   .0975542     9.27   0.000     .7117351    1.095957
------------------------------------------------------------------------------
```

Reference Group: Type 3

```
. regress Sum_Count clus4_dum

      Source |       SS       df       MS              Number of obs =     299
-------------+------------------------------           F(  1,   297) =    1.28
       Model |  1.3542485     1  1.3542485           Prob > F      =  0.2580
    Residual |  313.200935   297  1.0545486           R-squared     =  0.0043
-------------+------------------------------           Adj R-squared =  0.0010
       Total |  314.555184   298  1.05555431           Root MSE      =  1.0269

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus4_dum |   .1369362   .1208377     1.13   0.258    -.1008704    .3747427
       _cons |    .740113   .0771874     9.59   0.000     .5882094    .8920166
------------------------------------------------------------------------------

. regress Sum_Count clus5_dum

      Source |       SS       df       MS              Number of obs =     331
-------------+------------------------------           F(  1,   329) =    4.26
       Model |  3.55067467     1  3.55067467           Prob > F      =  0.0399
    Residual |   274.38286   329  .833990456           R-squared     =  0.0128
-------------+------------------------------           Adj R-squared =  0.0098
       Total |  277.933535   330  .842222833           Root MSE      =  .91323

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus5_dum |  -.2076455   .1006347    -2.06   0.040     -.405614   -.0096769
       _cons |    .740113   .0686426    10.78   0.000     .6050792    .8751468
------------------------------------------------------------------------------
```

Reference Group: Type 4

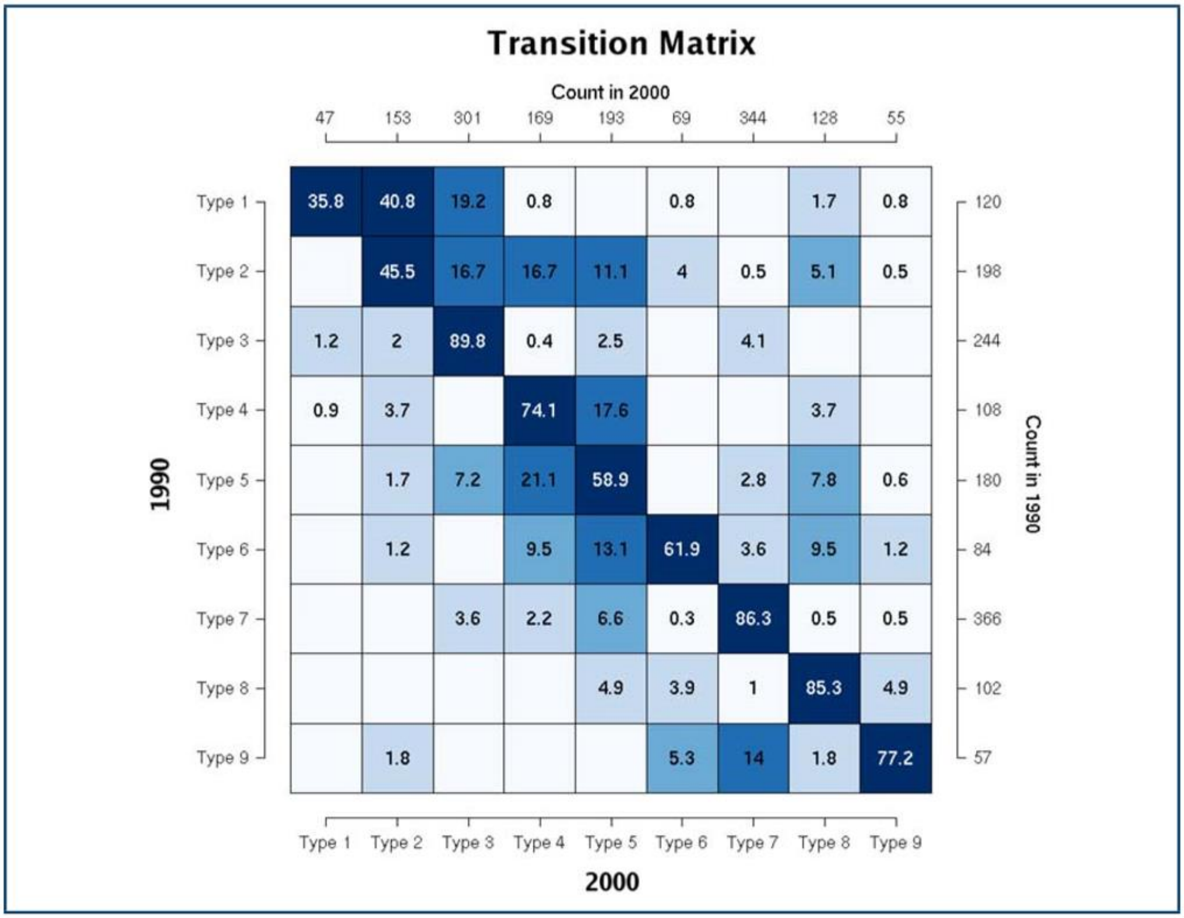
```
. regress Sum_Count clus5_dum

      Source |       SS       df       MS              Number of obs =     276
-------------+------------------------------           F(  1,   274) =    8.95
       Model |  8.08268691     1  8.08268691           Prob > F      =  0.0030
    Residual |    247.4934   274  .903260584           R-squared     =  0.0316
-------------+------------------------------           Adj R-squared =  0.0281
       Total |  255.576087   275  .929367589           Root MSE      =   .9504

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus5_dum |  -.3445816   .1151916    -2.99   0.003    -.5713547   -.1178086
       _cons |   .8770492   .0860452    10.19   0.000     .7076555    1.046443
------------------------------------------------------------------------------
```

Appendix 7: STATA Outputs – Regressions of Neighborhood Change Tradeoffs

Reference Group: Type 2

```
. regress Sum_Count clus6_dum

      Source |       SS       df       MS              Number of obs =     113
-------------+------------------------------           F(  1,   111) =    2.80
       Model |  3.84846078     1  3.84846078           Prob > F      =  0.0971
    Residual |  152.594017   111  1.37472087           R-squared     =  0.0246
-------------+------------------------------           Adj R-squared =  0.0158
       Total |  156.442478   112  1.39680784           Root MSE      =  1.1725

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus6_dum |  -.6816239   .4073883    -1.67   0.097    -1.488891    .1256432
       _cons |   .9038462   .1149716     7.86   0.000     .6760222     1.13167
------------------------------------------------------------------------------

. regress Sum_Count clus8_dum

      Source |       SS       df       MS              Number of obs =     193
-------------+------------------------------           F(  1,   191) =   13.57
       Model |  13.6275453     1  13.6275453           Prob > F      =  0.0003
    Residual |  191.802506   191   1.0042016           R-squared     =  0.0663
-------------+------------------------------           Adj R-squared =  0.0614
       Total |  205.430052   192  1.06994819           Root MSE      =  1.0021

------------------------------------------------------------------------------
   Sum_Count |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   clus8_dum |  -.5330596    .144703    -3.68   0.000    -.8184807   -.2476385
       _cons |   .9038462   .0982639     9.20   0.000     .7100244    1.097668
------------------------------------------------------------------------------
```

Appendix 8: Neighborhood Transition Matrix, 1990-2000



Source: Weissbourd, Robert, Riccardo Bodini, and Michael He. 2009. Dynamic Neighborhoods: New Tools for Community and Economic Development. Chicago, IL. http://www.rw-ventures.com/ftp/DNT Final Report.pdf.